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# MEASURING RISK ATTITUDES IN A NATURAL EXPERIMENT: DATA FROM THE TELEVISION GAME SHOW LINGO

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# MEASURING RISK ATTITUDES IN A NATURAL EXPERIMENT: DATA FROM THE TELEVISION GAME SHOW LINGO

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**Abstract:** We use data from a television game show involving elementary lotteries and substantial prize money as a natural experiment to measure risk attitudes. We find robust evidence of substantial risk aversion. As an extension, we estimate the various models using transformations of the "true" probabilities to decision weights. The estimated degree of risk aversion increases further, while players tend to substantially overestimate their chances of winning. CRRA and CARA utility specifications perform approximately equally well, with CARA having the advantage that the players' decisions do not depend on their initial wealth.

**Keywords:** LINGO, risk aversion, expected utility, decision weights, natural experiments.

**JEL codes:** D81, C90.

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# 1 Introduction

Risk attitudes play a critical role in determining the demand for insurance as well as the demand for risky assets and the equilibrium returns on these assets. Despite the importance of risk preferences, we still have very little idea about the answer to empirical issues like the average risk aversion of individuals, the determinants of risk atttitudes and the heterogeneity among individuals. The empirical findings depend to a large extent on the particular methods used to investigate these issues. Friend and Blume (1975) obtain indirect evidence about the degree of risk aversion from individual asset holdings. They estimate the coefficient of relative risk aversion (RRA) at roughly between 2 and 3. Other indirect evidence is provided by the equity premium puzzle. The observed spread between average stock returns and the risk free interest rate can only be consistent with an expected-utility maximising framework if we assume extreme degrees of risk aversion, usually around 20.[1] Campbell (1996) shows that the puzzle is compounded if one includes human capital in measured wealth and if one allows for mean reversion in the asset returns.

Direct evidence on the degree of risk aversion is obtained by Gertner (1993) from data on the television game show "Card Sharks". Although somewhat higher, his risk-aversion estimates are comparable to Friend and Blume's (1975) estimates. In another natural experiment, based on the television game show "Jeopardy", Metrick (1995) concludes that players display near risk neutrality. Finally, in an experiment in which Chinese students are presented with basic lotteries, Kachelmeier and Shehata (1992) find large differences between how much individuals are willing to pay for a lottery and for how much they are willing to sell the same lottery. This suggests that revealed risk preferences depend on the way problems are framed.

In this paper we use data from the television game show LINGO to measure risk attitudes. LINGO is a game show on Dutch television which is played by couples (usually friends, family or colleagues) over a maximum number of five rounds. Each round involves solving a word puzzle. At the start of each round, the couple decides whether to stop, or to continue and try to solve the word puzzle. If they stop they take home what they have won so far, while if they continue either their wins double or they lose everything and the game is over. In the latter case they can come back

[1] Mehra and Prescott (1985) contains the original statement of the equity premium puzzle. Kocherlakota (1996) and Campbell, Lo and MacKinlay (1997) provide an overview of the literature. The latter also summarise the empirical results for the United States.

in next day's show, with a maximum of three appearances.

For several reasons LINGO can be seen as a natural experiment for measuring risk attitudes. First, the decisions that a couple has to take are extremely simple, because LINGO is a non-strategic game which effectively reduces to a sequence of elementary lotteries in which the probability of winning declines over the rounds. Second, the decisions involve serious amounts of money for most players. On average, a couple takes home over 5,000 Dutch guilders (1 Dutch guilder (*f*) is approximately \$0.6). Finally, the game has been played so often that any learning effects can be reasonably assumed away. All this contributes to the validity of the assumption that players make decisions that reveal their true risk preferences.

We estimate constant relative risk aversion (CRRA) and constant absolute risk aversion (CARA) utility specifications for the players. In both cases we find robust evidence of substantial risk aversion. As a special case of CRRA utility, we follow Kahneman and Tversky (1982) by estimating the power utility function which assumes that individuals' utility is defined in terms of gains (and losses) rather than final wealth. Our estimate of the CRRA coefficient squares rather well with what they find. However, in contrast to what power utility predicts for these simple lotteries, we find that the stake plays a very important role in the decisions of the players. In particular, as the stake increases the willingness to continue decreases, ceteris paribus. This effect can be captured in the case of CRRA utility by assuming that gains are measured relative to some reference wealth level (usually initial wealth), or by estimating a CARA utility specification, which has the advantage that decisions are independent of initial wealth.

Because individuals' wealth levels are unobservable, the CRRA specification contains both the coefficient of relative risk aversion (RRA) as well as the reference wealth level as parameters. It is hardly possible to identify these two parameters separately. Therefore, we estimate the RRA coefficient while conditioning on different values of reference wealth. The estimate of the coefficient increases in reference wealth. This is reminiscent of Campbell's (1996) finding that the RRA coefficient needed to explain the equity premium puzzle becomes even higher if one also allows for human capital as part of an individual's wealth. For our data, if we set wealth at *f*50,000, we obtain an estimate of the RRA coefficient of approximately 6.5, which is well above the classical risk aversion estimates of Friend and Blume (1975), but below Campbell's (1996) estimates of the degree of risk aversion.

The number of studies that use an experiment with high monetary stakes and so many observations to obtain direct estimates of risk aversion is very small. Closest in spirit to our paper is the work by Gertner (1993). Qualitatively speaking, we confirm most of his findings using an independent (and larger) data set of a game which is even much simpler. However, we also extend his work in a number of ways. First, we take explicit account of the effect of the option to take decisions in future rounds on the optimal decision in the current round. Second, we compare the predictive power of decision models based on expected utility maximisation with decision models based on "rules of thumb" (i.e., simple rules linking decisions to directly observable statistics from the game). Despite the functional restrictions imposed by the expected utility model, we find that its performance in predicting decisions is comparable to that for rules of thumb.

A third extension is that we also estimate the expected utility models with subjective probabilities rather than the "true" probabilities. The subjective probabilities are the implicit decision weights that players use in calculating their odds. It turns out that players tend to overestimate their winning chances substantially. To nevertheless explain that players do indeed sometimes stop, the estimated degree of risk aversion increases further. The subjective survival probability is increasing in the true survival probability, although at a rate which is much less than proportional.

Although some people might question the appropriateness of estimating the degree of risk aversion while allowing for biases in the assessment of survival probabilities, we believe that these are two distinct issues.[2] Given the assessment of their odds, however wrong they may be, individuals take decisions according to their personal risk attitudes, which is what we try to quantify. In the context of the present game, mistakes in the assessment of the survival chances may arise for various reasons. The most likely is that players systematically overestimate their ability to solve the word puzzles in LINGO. Indeed, there is a substantial amount of evidence that individuals tend to be overconfident when taking decisions under uncertainty.[3] A second possible explanation is that players possess bounded rationality as far as complex computa-

[2] It is sometimes argued that transformations of probabilities should be considered as an integral part of an individual's risk attitudes (see Wakker, 1994).

[3] Tversky and Kahneman (1974) and Arrow (1982) provide overviews of common biases in people's assessments of probabilities. Camerer (1987) explores such biases in the context of an experimental market. Gneezy (1997) presents evidence on the failure of individuals to adjust the perceived probability distribution of final outcomes when a game or lottery is played repeatedly.

tions of their odds are concerned.[4] However, it is hard to see how this could lead to a systematic bias in the perceived odds. It would only add some randomness to the perceived probabilities. We will account for this effect in the empirical model. These explanations can be perfectly consistent with psychological models of decision making under uncertainty. In fact, replacing probabilities with decision weights is one of the key elements of prospect theory (see Kahneman and Tversky, 1979, 1982, and Tversky and Kahneman, 1992).

We emphasise that the substantial degree of risk aversion we find is likely to be only a lower bound on the true degree of risk aversion. There are three reasons for this conjecture. First, people who participate in LINGO probably like these types of games. If anything, this should induce them to continue playing longer than they otherwise would. Secondly, there may be a camera bias which also induces them to continue longer than they otherwise would prefer to. In other words, playing the game and being on television might be part of peoples' utility. These effects are partly captured by estimates we obtain for the option value of coming back the next day in the case of first and second finals. This option captures both the expected monetary gains when coming back, but also the utility of playing the game, or of being on television once more. To take care of these potential biases we also estimate the model exclusively on third finals. A third reason why the estimated degree of risk aversion may be lower than it actually is, is the "gambling with the house money" effect (see Thaler and Johnson, 1990): players have not yet got accustomed to the money they have won so far and are, therefore, more willing to bet their stakes.

The remainder of the paper is structured as follows. Section 2 describes the game, while Section 3 describes the data and provides summary statistics. In Section 4 we estimate decision models based on rules of thumb. Indeed, directly observable statistics go quite a long way explaining observed decisions. Section 5 provides the theory for the estimation of the expected utility maximisation models. In particular, we show that due to the particular structure of the game, the players' multi-stage decision problem can be effectively reduced to a single-stage decision problem (under very weak conditions). Section 6 yields the empirical results for the estimation of the expected utility models. We compare also the predictive power of the various models (including the decision models based on rules of thumb). Section 7 estimates the expected utility models while allowing for differences between the players' per-

[4] For a recent survey on bounded rationality, see Conlisk (1996).

ceived odds and their "true" odds. Finally, Section 8 concludes the paper and offers suggestions for further research.

## 2 The Game

LINGO is a word game which is played almost every day on Dutch television. By July 1997, it has been played more than 1350 times. Each play involves a "pre-final" and a "final". In the pre-final two couples have to guess five-letter words. For each word they guess correctly the couple receives $f50$. The couple which has solved the most five-letter words at the end of the pre-final progresses to the final. The other couple goes home with the money it has won.

Our main interest is in the final. The final is played over a maximum number of five rounds. In essence, each round involves an elementary lottery, as depicted in Figure 1. The couple enters the round with a particular stake. For the first round this is the amount of money won in the pre-final (excluding the amount won from the "jackpot" – see below). At the start of each round the couple decides whether to continue or to stop. If they stop, they take home their current stake. If they continue, they must play a lottery. If they win the lottery, their stake for the start of the next round doubles, but if they lose, all money is lost. In that case, the game stops and the couple is allowed to come back the next show unless this is their third, and last, final. If they come back they play again a pre-final against another couple, in which they either drop off, or win and enter the next final.[5] Once a couple has stopped, or won the lottery in all five rounds, they are not allowed to come back.

The actual game in each round of the final again involves guessing a five letter word. The maximum number of attempts for each word is five. The number of attempts determines the number of balls a couple has to draw from an urn. Consider the board in Figure 2. At the start of the final each of the open boxes, *i.e.*, those not filled with an **X**, contains some number. For each attempt needed to guess the word in some round the couple has to draw a ball (without replacement) from the urn. If they have not solved the puzzle in five attempts, they must draw the maximum number of six balls. The urn contains 35 numbered balls and one *golden* ball. If the number of a ball they draw corresponds to the number in one of the open boxes, this box is filled with an **X**.[6] If they draw the golden ball, they stop drawing and go

[5] The next show is usually recorded within an hour time, but is shown on television the next day.
[6] For each of the nine "numbers" in the white boxes there is a ball in the urn which contains the

immediately to the start of the next round. Once one row, column or the diagonal of the board is completely filled with **X**'s, the game is over and the players lose their stake. If this happens, we will say that the players "get LINGO".

In the pre-final there is also a "jackpot", which increases by *f*50 after each correctly guessed word. After each word they solve, a couple can draw two balls, without replacement, from an urn containing green and red balls. The jackpot accumulates over the shows until some couple has drawn three green balls in a pre-final. This couple receives the amount in the jackpot, which starts at zero again. Gains from the jackpot are not at risk in the final. However, when the jackpot has risen to a high value, this may provide an incentive to continue longer in this final, because the failure to survive this final (if it is not the third final) yields another attempt at the jackpot in the next pre-final.

Summarising, LINGO provides a natural experiment for measuring risk attitudes, because at the start of each round in the final players face a very simple decision problem whether to continue or not. The survival probabilities are decreasing over the rounds, which induces players to stop if the odds become too unfavourable. Figure 3 summarises the possible ways in which a couple can go through the game from the moment that it first enters the stage. It also shows all the potential sources of its total accumulated gains at the moment that it leaves the game.

# 3 Data and Descriptive Analysis

Most of the data were generously provided by the producer, ID$^{TV}$. The remainder of the data were obtained by watching the program on television.[7] We used observations from finals 633 through 1366. This is a total of 734 finals, but of course this constitutes a much larger number of decisions, given that each final can last for up to five rounds.

Table 1 shows some key summary statistics for the finals. The entries only refer to the players who appear in the final. Candidates are selected on the basis of their ability to guess words and their appearance on television. Hence, there is no apparent link between the selection criterion and their risk attitude. For most of the couples we know their gender. Females are clearly overrepresented in this game. For more

same number.

[7] ID$^{TV}$ keeps a record of the course of each final. These records are used by its accountant for the official tax statement. These data should be of high quality, which is confirmed by comparing them with our observations from television.

than 25% of the finals we know the ages of the players. By far, most of them are in their twenties or thirties. Players younger than twenty and older than sixty-five are very rare. We also know the education level and profession for about one fourth of the participants. From this it appears that students are overrepresented. We have little idea how the composition of the sample will affect our measures of risk aversion. Some indications come from a survey study among Dutch people by Hartog and Jonker (1997). Respondents were asked the amount they were willing to pay for a lottery ticket that has a probability of 10% of winning $f1000$. From the answers Hartog and Jonker (1997) construct a measure of absolute risk aversion. They find that women are more risk averse than men and that schooling level reduces risk aversion.

The amount of money in the jackpot can be quite substantial, as indicated by the maximum of $f20450$ it once reached. W0 is the initial stake in the final (which thus excludes the gains from the jackpot), while W1 is the amount of money gained in the final. The average gains per couple is $f5158$, which would be quite a serious amount of money for most.

An important input for calculating the odds in the lotteries is the ability of couples in solving the word puzzles. Table 2 gives the frequency distribution of the number of balls that had to be drawn in each of the rounds of the observed finals. We tested for many different ways of splitting the sample to search for heterogeneity in ability. Gender differences, age, or number of appearances in the final do not significantly alter the ability distribution. The null hypothesis of the distributions being equal could only be rejected for a split according to the amount a couple has won in the pre-final round. The table shows the distributions for W0 $\leq>$ 400 guilder. Even here the differences are small. Since we cannot find reliable instruments for possible heterogeneity in ability, we make the assumption that all couples have the same ability in solving the word puzzles.

Table 3 separates the first, second and third finals into the percentage of couples that continued and survived all five rounds (WINNER), those who stopped before or at the end of the fourth round (STOPPER), and those who got nothing this game (LOSER). As is clear from the table, the percentage of losers falls, while the percentage of stoppers increases with the number of appearances in the final. This indicates that people are less willing to take risks, if they run out of possibilities to return. Of the losers in the first final 49% (= 173/356) managed to come back into the second final, while 54% (= 61/114) of the losers in the second final returned into the third final. As this means that the probability of winning against a random couple in the next pre-final is about one half, there must be only minor differences in abilities across the couples participating in the game.

An important input for the decisions are the odds at which couples play the next lottery. The probability $P_k(j,n)$ of surviving with the next $j$ balls conditional on having already drawn $n$ balls and having $k$ direct possibilities of getting LINGO are computed in Appendix A (available upon request from the authors). Using the overall ability distribution $f_j$ from Table 2 we compute the probability of surviving the next round as

$$\text{PROB} = \sum_{j=1}^{6} f_j P_k(j,n). \tag{1}$$

Table 4 shows summary statistics of the probabilities at which the players decided to stop, and at which they decided to play. On average couples stop at survival probabilities well above a half. We almost never observe them playing at probabilities less than a half. Some couples are apparently so risk averse that they stop at a survival probability of 0.86.

# 4 Decisions Based on Rules of Thumb

This section contains an exploratory data analysis of the variables players may use in their decisions. Before turning to decision rules based on expected utility maximisation (in the next section), we will therefore study possible "rules of thumb" that players might use in deciding whether to stop ($y_i = 0$) or to continue ($y_i = 1$). We interpret a rule of thumb as a simple decision rule based on an indicator $y^*$ which is a function of variables that can be observed immediately or that can be computed with extremely little effort. This indicator captures the relative weights that players attach to these variables in order to take their decisions.

The most interesting decisions are the last decisions in each show and, in shows where the players decided to stop, also the next-to-last decision. The last decisions of winners and losers give an indication of an upper bound on their risk aversion, while the final two decisions of stoppers jointly give an upper and a lower bound on their risk aversion. Our data set of decisions thus includes stoppers in a given final twice (the round they stop and the round before that, when they still decided to continue) and the other couples once (their last "play" decision, whether they win or lose). The total number of observations is 888. We assume that all error terms are uncorrelated, even though we sometimes observe multiple decisions by the same couple.[8]

Table 5 shows the results of probit regressions. The explanatory variables are:

**STAKE:** the amount of money at stake at the moment the decision is to be taken. It is included, because at given odds a larger stake increases the riskiness of the bet as measured by the variance of the outcomes. For this reason, we would expect STAKE to have a negative effect.

**FINAL:** the number of finals (including this one) played by the candidates. If FINAL is higher, the number of possibilities to come back is reduced, which should discourage the players from continuing. This suggests that FINAL has a negative effect.

**BALLS:** the number of balls still in the urn. A larger value of BALLS raises the survival probability and, hence, we expect its effect to be positive.

**BAD:** the number of positions on the board that give LINGO directly (either 1, 3 or 5, see Appendix A) is expected to have a negative effect.

**LAST:** this variable is included as a test for heterogeneity. If teams differ in their risk attitudes, then the more risk averse players will stop earlier. That means that in later rounds of the game players with less risk aversion are overrepresented. Because they are less risk averse on average we expect teams to be more willing to play in later rounds, ceteris paribus.

**W0:** the initial stake in this final may serve as a proxy for the ability to solve word puzzles. Ceteris paribus, better players would have an incentive to stop later, which suggests that it has a positive effect.

**PROB:** the survival probability. If players in fact base their decisions on a rule of thumb, then PROB should not have any independent explanatory power. It might also be too complicated to calculate or estimate PROB on the spot. Since PROB is a function of BAD and BALLS (though highly nonlinear), players who could somehow estimate their survival probabilities, would no longer

[8] The possible correlations will have no easy pattern, since we can have multiple observations of the same team for several reasons. Either a couple has stopped in their first appearance in the final (2 observations), or the observations span multiple shows (when they lose in the first final, but return the next day).

need to base decisions on BAD or BALLS separately, once they know PROB. This suggests that either PROB, or the combination of BAD and BALLS is redundant.

The first line in Table 5 does not include PROB, and thus tries to explain decisions by employing only variables that are directly observable by the players. Except for the constant, all explanatory variables are significant. Their coefficients also have the expected sign, including LAST, which suggests the possibility of heterogeneity in risk attitudes. The second line in the table drops LAST as explanatory variable. The results are similar to those obtained for the previous regression, except for the fact that W0 is no longer significant. We have also included the jackpot at the start of the next pre-final as a regressor in the various specifications. In none of the cases the jackpot had significant explanatory power. Therefore, we do not report these results.

To see whether we can refute the hypothesis that players follow simple rules of thumb, we add PROB to the first regression equation. Clearly, PROB has no independent explanatory power whatsoever (line 3 of 5). The insignificance of the individual coefficients of all variables BALLS, BAD and PROB indicates the strong multicollinearity among these variables. In the final regression (line 4 of Table 5) we drop BALLS and BAD as regressors. While the other coefficients are basically unaffected, PROB now becomes highly significant.

Summarising, the results we obtain for the simple regressions above may well indicate that studying simple rules of thumb may not be so bad in a first attempt to build a descriptive model of the players' decisions. The results also suggest that players take account of their odds by basing their decisions on variables which are highly correlated with the survival probabilities computed with the help of (1). Finally, the option value of coming back in first and second finals plays an important role in the decisions through the variable FINAL.

# 5 Expected Utility Maximisation

We turn now to the analysis of decision models based on expected utility maximisation. We are interested in how well decisions can be explained using utility functions that are often employed in economic analysis. Moreover, we would like to know how well these models perform when compared with the decision models based on rules of thumb, which we estimated in Section 4. The main objective of the expected utility analysis is to obtain estimates of the degree of risk aversion.

The decision problem faced by the players seems complicated, because it may be followed by other decisions. One such complicating factor is the possibility to return the next show after losing today. Instead of getting zero, one can expect to gain something from tomorrow's game. The return possibility can be seen as an option which affects decisions in this show whether to stop or continue. The other option element is the possibility to decide again in the next round of this final. For example, suppose that the game has evolved until the start of the second round. The decision to stop would eliminate the possibility to make a similar decision at the start of the third round and could therefore affect the decision taken at the start of the second round. In general this aspect would require dynamic programming techniques to solve for the optimal stopping rule.

In this section, we provide some theoretical results pertaining to the specific game under consideration. In particular, we show that, because of the (weakly) decreasing survival probabilities over the rounds, the decision problem reduces, under rather weak conditions, from a multi-stage dynamic programming problem to the choice between receiving the current stake with certainty and a single elementary lottery. This simplifies the analysis of the game considerably, and motivates the econometric model.

We start the analysis by considering a single-round game, which could be the last round of an actual game. Let $U(x)$ be the utility that a couple gets from receiving amount $x$.[9] Figure 3 (see Section 2) shows the decision tree for the one-round game. At the start of the round the stake is $x$. The probability of surviving this round is denoted $p$. As explained in Appendix A this probability depends on the *state* of the game. The state is determined by the number of balls drawn so far and what has happened on the LINGO board (see Figure 2). If the players decide to stop, they keep $x$ with certainty. If they continue, they receive $2x$ with probability $p$, while they expect to receive $a$ with probability $1-p$. The amount $a$ represents the option value of the potential earnings in future games. If they cannot come back (because it is their third final), then $a = 0$.

Denote by $V(A)$ the expected utility from action $A = 0$ (stop) or $A = 1$ (continue)

[9] This assumes that the two players that form a couple have the same utility function, which implies that they do not disagree about the decision to be taken. In fact, when watching the show on television we very rarely observe disagreement about whether to continue or to stop. Moreover, we assume that they share their gains equally. Because we have no way of knowing how they actually share their gains, this seems to be a rather natural assumption.

at the start of the single-round game, so that

$$\begin{aligned} V(0) &= U(x), \\ V(1) &= (1-p)U(a) + pU(2x). \end{aligned} \tag{2}$$

If $x \leq a$, it is always optimal to continue. Throughout this section we will therefore assume that $x > a$. The players will decide to stop if $V(1) < V(0)$, or equivalently if $p$ is smaller than the critical probability $p^*$ given by

$$p^* = \frac{U(x) - U(a)}{U(2x) - U(a)}. \tag{3}$$

Observe that $p^*$ is decreasing in $U(a)$, which means that continuing becomes relatively more attractive the higher is the utility from returning the next day. If $x < a$, we define $p^* = 0$, and players will always continue.

In the empirical analysis we will use two different utility functions. The first is the constant relative risk aversion (CRRA) specification

$$U(x) = \frac{(W+x)^{1-\gamma} - 1}{1-\gamma}, \qquad \gamma > 0, \tag{4}$$

where $W$ acts as reference level against which the gains in this final will be evaluated. We assume that $W \geq 0$ and $\gamma > 0$. Moreover, if $W = 0$, then $0 < \gamma < 1$, while $\lim_{\gamma \to 1} U(x) = \ln(W + x)$. The critical probability $p^*$ follows as

$$p^* = \frac{(W+x)^{1-\gamma} - (W+a)^{1-\gamma}}{(W+2x)^{1-\gamma} - (W+a)^{1-\gamma}}, \tag{5}$$

showing that the optimal stopping rule will depend on all parameters ($x$, $W$, $\gamma$, $a$).[10]

$W$ can have several possible interpretations and will, therefore, be referred to as the *reference wealth level.* Strictly speaking, under expected utility maximisation $W$ would be interpreted as the wealth level at the start of the final. Because initial wealth may well differ across couples and because it is unobservable, it is less suitable in the empirical work.[11] When we use the CRRA function we must therefore treat

[10] If a couple shares their gains equally, each would have a utility $U(x/2)$, and an initial wealth $W/2$. Since (5) is homogeneous of degree zero in $x$, $a$, and $W$, decisions based on individual utility or team utility will be the same.

[11] For many players we do know their eduction, profession and age. From these we can make some guess about their individual wealth. But such data will be extremely noisy. Moreover, many female participants write "housewife" as their occupation, so that we do not have any clue about relevant household wealth.

$W$ as a parameter and interpret it as the average level of wealth of our sample. This is an important drawback of the CRRA utility function.

In the prospect theory developed by Kahneman and Tversky (1979) individuals attach utility, or more precisely "value", to gains and losses relative to initial wealth rather than final wealth. In that case, $W = 0$ and the CRRA specification reduces to the power utility function:

$$U(x) = \frac{x^{1-\gamma} - 1}{1-\gamma}, \qquad 0 < \gamma < 1. \tag{6}$$

In their experiments Kahneman and Tversky (1982) find support for (6) as a description of individuals' evaluation of gains ($x > 0$). The current specification thus assumes that utility depends purely on the amount of money won in this final. A very special case is the power utility function for teams in the third final (when $a = 0$). In that case $p^* = \frac{1}{2}^{1-\gamma}$, so that decisions will be independent of the stakes of the lottery. In all other cases the stakes will matter. From our descriptive results in Section 4, however, we have already seen that even in third finals the decisions do depend on $x$.

The other type of utility function that we consider is constant absolute risk aversion (CARA):

$$U(x) = -\frac{1}{\gamma}\exp(-\gamma(W + x)), \qquad \gamma > 0. \tag{7}$$

Parameter $\gamma$ now denotes the coefficient of absolute risk aversion. Using the data from their survey, Hartog and Jonker (1997) conclude that CARA is a reasonable description of the risk attitude of individuals with financial wealth of up to Dfl. 100,000. This is substantially higher than average household wealth in the Netherlands.

The different implications of the CARA utility function can be seen by computing the critical probability $p^*$,

$$p^* = \frac{\exp(-\gamma x) - \exp(-\gamma a)}{\exp(-2\gamma x) - \exp(-\gamma a)}, \tag{8}$$

which does not depend on wealth $W$. Risk neutrality corresponds to the limiting case with $\gamma \downarrow 0$. To see this, apply l'Hôpital's rule on (8), to obtain,

$$\lim_{\gamma \downarrow 0} p^* = \frac{x - a}{2x - a}. \tag{9}$$

The right-hand side of this equation is the probability $p$ for which a risk-neutral person is indifferent between receiving $x$ with certainty, or $2x$ with probability $p$ and $a$ with probability $(1 - p)$.

Next consider Figure 4, which shows a two-round game. At the start of the first round the couple either stops and takes home $x$ with certainty, or they continue. In the latter case, they survive with probability $p_1$ and lose with probability $1 - p_1$. If they win the round one lottery, they enter the second round, where the game is of the same format as the single-round game analysed above, although with a probability $p_2$ instead of $p_1$, and an initial stake of $2x$. The expected value of coming back, given by $U(a)$, remains the same during the two rounds. The survival probability $p_2$ at the start of the second round is unknown at the start of the first round. Hence, the expected utilities from stopping or continuing at the start of the first round of the two-round game are given by,

$$\begin{aligned} V_2(0) &= U(x), & (10) \\ V_2(1) &= (1-p_1)U(a) + p_1 \mathsf{E}\left[\max\left\{U(2x), (1-p_2)U(a) + p_2 U(4x)\right\}\right], & (11) \end{aligned}$$

where the expectation in (10) is taken over the unknown survival probability $p_2$ at the start of the second round. The subscript on the value function $V_n(.)$ indicates that we are evaluating an $n$-round game. Hence, $V_1(A) = V(A)$ in (2). It follows immediately that:

$$\begin{aligned} V_2(0) &= V_1(0) \\ V_2(1) &\geq (1-p_1)U(a) + p_1 U(2x) = V_1(1) \end{aligned} \tag{12}$$

Hence, if it is optimal to continue at the start of the single-round game ($V_1(1) > V_1(0)$), it is also optimal to continue at the start of the two-round game.

Define the round $k$ critical probability $p_k^*$

$$p_k^* = \frac{U(2^{k-1}x) - U(a)}{U(2^k x) - U(a)}, \qquad k = 1, \ldots, n. \tag{13}$$

The critical probabilities have the following useful properties:

**Lemma 1** *For both CRRA and CARA utility functions the critical probabilities weakly increase per round:*

$$p_{k+1}^* \geq p_k^* \tag{14}$$

*Also, for the CRRA function, for given $x$, $p^*$ is decreasing in $W$, while for given $W$, $p^*$ is increasing in $x$.*

Proof of the lemma follows by straightforward algebra, and is given in Appendix B (available upon request). The lemma does not hold in general for any utility function, though.

We can now state the main result of this section, which is summarised in the following proposition:

**Proposition 1** *If $p_2^* \geq p_1^*$, the optimal decision at the start of the first round of the single-round game is the same as the optimal decision at the start of the n-round game.*

**Proof:** Here, we give the proof for the two-round game only. This serves as the first step of the induction argument for the general case, which is contained in Appendix C (available upon request). We have already seen in (12) that, if it is optimal to continue at the start of the single-round game, it is also optimal to continue at the start of the two-round game. Suppose now that $p_1 < p_1^*$, so that it would be optimal to stop at the start of the single-round game. Since $p_2 \leq p_1$ and $p_1^* \leq p_2^*$, one has that $p_2 \leq p_2^*$. Hence, by definition of $p_2^*$, we have $\max\{U(2x), (1-p_2)U(a) + p_2U(4x)\} = U(2x)$. Therefore, $V_2(1) = (1-p_1)U(a) + p_1U(2x) = V_1(1) < V_1(0)$.

# 6 Empirical Results for Expected Utility

In this section we will present estimates of decision models based on expected utility maximisation. As we already noted, we assume that all players have the same utility function. We assume also that all couples have equal abilities in guessing five-letter words and, therefore, equal survival probabilities (for a given state of the game). Ideally, one would want to relax these assumptions. However, we do not have any reliable instrumental variables to discriminate between risk attitudes and abilities.

In Section 5 we showed that, due to the special structure of the game, under very weak restrictions (see Proposition 1), the players' decision problem reduces to an elementary lottery. Expected utility maximisation then motivates the following PROBIT model for the stop/play decision,

$$y_i^* = p_i - p_i^* + \epsilon_i, \tag{15}$$

with observations $y_i = 0$ (stop) if $y_i^* < 0$ and $y_i = 1$ (continue) if $y_i^* \geq 0$. Teams will play, if the survival probability $p_i$ exceeds the critical survival probability $p_i^*$. The error term $\epsilon_i$ is assumed to be normally distributed with mean zero and variance $\sigma^2$. The parameters of the model are the degree of risk aversion $\gamma$, the option value of returning for teams in the first or second final ($a_1$ and $a_2$), reference wealth $W$ (for CRRA utility), and the error variance $\sigma^2 = \mathsf{E}[\epsilon_i^2]$.[12] The error term could capture a variety of effects. One would be the presence of non-systematic errors in the assessment of the survival probability. Another would be that individuals make mistakes in their choices even when they know their odds. Finally, the error term may arise from the presence of heterogeneity among the players which is not systematically linked to their survival probabilities.

Table 6 shows the estimates for the CRRA utility specification. The first row in the table shows the results for a power utility specification ($W = 0$). This specification assumes that players' utility is determined only by the gains from the game, without any reference to their level of wealth. The estimate of $\gamma$ of 0.41 is highly significant (conditional on $W = 0$), and indicates a strong rejection of risk neutrality ($\gamma = 0$).

The other rows of the table report estimates of $\gamma$ for different levels of reference wealth in order to demonstrate the dependence between $\gamma$ and $W$. When we increase the wealth parameter, the estimate for $\gamma$ also increases. With wealth equal to $f$50,000, the relative risk aversion parameter increases to 6.66. All these models with wealth in excess of $f$10,000 fit the data about equally well. This multicollinearity arises because the informative stakes in the games are mostly concentrated in a range between 2000 and 5000 guilders. Within this range the functions $-(10+x)^{-0.97}$ and $-(50+x)^{-5.66}$ imply very similar critical probabilities $p_i^*$.

This is illustrated by the following example. Consider a lottery with $f$4000 at stake ($x = 4$). A person with a low wealth $W = 10$ will play the lottery if the probability of winning is larger than $p^* = 0.64$. Someone with the higher wealth $W = 50$, but the same relative risk aversion will always play the lottery at this probability, since the stake is relatively low compared to his higher wealth. In order to obtain a critical probability $p^* = 0.64$ when the reference wealth level is $f$50,000, a person must have a higher risk aversion coefficient. Indeed, when $\gamma = 6.66$, the critical probability for the 4000 guilder lottery is 0.65, almost equal to the critical probability at ($W = 10$, $\gamma = 1.97$). Over the range of stakes that we see in the data, the combination of low wealth and a low risk aversion coefficient implies the same behavior as high wealth and

[12] Contrary to standard PROBIT model the residual standard error $\sigma$ is identified. Equivalently, we could have written $y_i^* = \beta(p_i - p_i^*) + \epsilon_i$ with the variance of $\epsilon_i$ normalised to one.

a high risk aversion coefficient. Unrestricted estimation of the CRRA model does not allow us to identify $W$ and $\gamma$ separately. The wealth level of $W = 50$ is representative for household wealth in the Netherlands.[13] Hence, if the participants of LINGO are representative for the Dutch population, a relative risk aversion parameter of $\gamma = 6.66$ would be our best guess.

The results displayed in Table 6 are reminiscent of the findings in the literature. In general, the literature has found that different measures of wealth have major effects for asset pricing models. For example, Campbell (1996) finds that if the measure of wealth is increased by including human wealth, the estimate for the CRRA coefficient increases substantially. Jagannathan and Wang (1996) study a cross section of stock returns and find that the estimates of the conditional Capital Asset Pricing Model are substantially improved by including a measure of human capital in investors' wealth.

Parameters $a_1$ and $a_2$ are the estimates of the "guilder certainty equivalent" values of coming back when playing the first and second final, respectively. That is, $a_1$ is the amount of money that players would be willing to pay to be allowed to come back after the first final. The estimates for $a_1$ and $a_2$ are both highly significant and sizable, indicating that the possibility to come back plays an important role in the decisions taken. Note also that $a_1 > a_2$, as required by the model.

The relatively high (compared to the amount of money won on average) estimates that we obtain for $a_1$ and $a_2$ suggest that players not only derive utility from the monetary gains. If participants also attach utility to the fun of playing LINGO and being on television, they will continue longer, because this gives them the opportunity to play the game and be on television again the next day. Our model combines the utility of playing the game with monetary gains in the "option values" $a_1$ and $a_2$. To see whether the possibility to return invites different behavior, we re-estimated the risk aversion parameter on the subsample of third finalists. These teams cannot return the next day anymore.

Table 7 reports the results. Because the number of observations is so small, the estimates are rather imprecise. Nevertheless, the point estimates confirm substantial risk aversion.[14] A caveat with the third final subsample is that it might be subject

[13] Bloemen (1997) estimates median household wealth in the Netherlands at approximately ƒ50,000 in 1993 and 1994.

[14] Incidentally, the unconstrained maximum likelihood estimator converges to $\hat{W} = 46.5$. The unconditional standard error for $\gamma$ turns out to be 100 times as big as the conditional standard error reported in the table due to the enormous multicollinearity.

to selection bias if there is heterogeneity in risk attitudes. People who enter the final for the third day in a row must have lost on the two previous days. This could select only those people who very much like to play the game, and/or are relatively less risk averse than the average player. This would lead to a lower estimate of risk aversion for the "third finals" subsample. The estimated value for $\gamma$ is indeed lower than for the full sample, but the difference is not significant.

The results for the CARA utility specification in Table 8 are very similar. The risk aversion parameter is significantly different from zero (risk neutrality). The option values and the fit are almost identical to those for the CRRA model. Without data on individual wealth $W_i$ the two specifications have similar implications for behaviour in the LINGO game.

To give an impression of what the estimates imply for an agent's risk attitude, Table 9 considers the choice between $x$ with certainty, or a lottery with payoff $2x$ with probability $p$ and a fixed amount $a$ with probability $1 - p$. The table shows that an agent with constant relative risk aversion, no reference wealth ($W = 0$ and thus $\gamma = 0.41$) would only be willing to take the gamble if the probability of winning ($p^*$) is at least 0.66. For the power utility function ($W = 0$) the critical probability does not depend on the stake $x$. Models with either $W = 10$ or $W = 50$ fit the data better, and imply that teams are more willing to play if the stakes are low. The critical probabilities are almost identical for the CRRA and CARA models.

A positive option value $a$ reduces the critical probabilities. Therefore, first-time finalists will always play as long as the stakes are below $a_1$. Even with stakes larger than $a_1$, first-time finalists should almost always continue. Only if the stakes are above 4000 guilders, do they require a survival probability that is more than one half. This usually does not happen until the fourth round of a final. The most informative data are therefore the decisions made by third time finalists, who cannot return.

A first step in evaluating the various models is to compare their ability to predict (in-sample) decisions. Since the CARA and CRRA utility functions fit the data about equally well, we will discuss the misspecification only for the CARA utility function. Table 10 compares the actual and predicted stop and play decisions. Given that the play frequency is 83%, the simplest possible model would always predict that the players continue. Hence, it delivers a correct prediction of all actual continuation decisions, but of none of the actual stop decisions. The expected-utility model performs better by correctly predicting 86% of all cases. The model has most problems in explaining why people stop, failing to generate the stop decision for more than half of the actual stoppers.

In Section 4 a rule-of-thumb model was estimated to describe the behaviour of teams. If utility maximisation provides a correct description of players' decisions, the expected-utility model should be able to encompass the rule-of-thumb specification. For this purpose we estimate the PROBIT model

$$y_i^* = \alpha\left(\frac{p_i - p_i^*}{\sigma}\right) + \beta z_i + \epsilon_i\,, \tag{16}$$

where $p_i - p_i^*$ is the difference between the actual and the critical survival probability computed at the maximum likelihood estimate for the CARA specification in Table 6.[15] When the probabilities are scaled by $\sigma$, the coefficient $\alpha$ should be equal to one, and all other explanatory variables in the vector $z_i$ in (16) should have zero coefficients. In effect, we are testing whether the residuals of the PROBIT model are orthogonal to the rule-of-thumb instruments.

Column 1 of Table 11 shows that the expected-utility model certainly beats the most naive decision rule, that people always play: the constant term is not significant. The second column indicates that the expected-utility model correctly captures the effects of the survival probability, the stake, the "comeback" options and the money earned in the pre-final stage of the show. Jointly and individually these variables do not add to the explanatory power of the expected utility model. However, despite that the estimate of $\alpha$ is so close to one, we find that LAST, which denotes the number of the round of the final in which the decision is made, W0, the initial stake, and STAKE, the current stake, are all significant in the last two columns of Table 11. The significantly positive sign of LAST indicates that people are more inclined to play the further the final progresses, ceteris paribus. Similarly, teams with a higher initial stake continue for longer, on average.

To provide an explanation for these findings, remember that due to data limitations we had to make two important simplifying assumptions: that agents are idential in their abilities as well as in their risk preferences. Barsky et al. (1997) provide information based on a survey which suggests that heteregeneity in risk preferences is potentially important.[16] The *combination* of W0 and LAST being significant may

[15] The other specifications give virtually the same results.

[16] Heterogeneity in risk preferences may help to explain why so few people are stockholders (see Mankiw and Zeldes, 1991), which on its turn might have important effects for the behaviour of asset returns.

be explained by the omission of both types of heterogeneity from our model. The effect of W0 is most likely an ability effect: players who enter the final with a larger initial stake are likely to be more able in guessing five-letter words. For such players the odds are more favourable than our estimated survival probabilities suggest. They would therefore continue for longer, even if they hold the same risk attitudes as their less-able counterparts. With heterogeneity in risk preferences, the population of players in later rounds of the final will on average be less risk averse. At given odds, such players are more likely to continue. Given that the significance of $W_0$ most likely captures the effect of heterogeneity in ability, heterogeneity in risk preferences may explain the significantly positive coefficient of LAST.

# 7 Decision Weights

Empirical evidence based on psychological models of behaviour suggests that individuals tend to be overconfident (see Tversky and Kahneman, 1974). In the context of LINGO such overconfidence would lead players to overestimate their abilities in solving word puzzles. As a result, the *perceived* survival probabilities would exceed the objective survival probabilities. To model systematic deviations between these probabilities and the weights that subjects give to alternative outcomes, (cumulative) prospect theory introduces the concept of decision weights (see Kahneman and Tversky, 1979, 1982, and Tversky and Kahneman, 1992). If people are overconfident, the decision weight attached to survival is larger than the objective survival probability. In that case people will tend to play longer than would be justified by their risk preferences. But the longer people play in the LINGO final, the lower our estimates of risk aversion. When we mistakenly model the decision rule using the objective survival probabilities, we will therefore obtain biased low estimates of the risk-aversion parameter.

Tversky and Kahneman (1992) and Benartzi and Thaler (1995) suggest the following transformation from probabilities $p$ to decision weights $\pi(p)$:

$$\pi(p) = \frac{p^\delta}{[p^\delta - (1-p)^\delta]^{1/\delta}}, \tag{17}$$

where $\delta$ is a parameter. This function generates an S-shaped relation between the probabilities and decision weights. Because it only has one parameter, it can only generate a limited range of the possible shapes for the transformation. Therefore, we will employ the following flexible double Logit transformation:

$$\begin{aligned}\pi(p) &= \frac{e^q}{1+e^q}, \\ q &= \frac{\ln\left(\frac{p}{1-p}\right)-\mu}{\omega}.\end{aligned} \tag{18}$$

Figure 5 shows some typical shapes of the transformation. A possibility is an S-shape similar to the one produced by 18. If $\mu = 0$ and $\omega = 1$, the transformation reduces to $\pi = p$. With $\mu = 0$, $\pi(p)$ is symmetric in $(\frac{1}{2}, \frac{1}{2})$. The function $\pi(p)$ crosses the $45^0$ line above (below) one half when $\mu$ is less (greater) than zero. In a sense, $\mu$ acts primarily as a shift parameter and allows for a systematic over- cq. underestimation of the probability. Parameter $\omega$ determines the curvature of the function $\pi(p)$. A decrease (increase) in $\omega$ leads to an overestimation over the probability if the probability is high (low). In other words, $\omega$ determines the sensitivity of the decision weight to changes in the probability in specific regions of the interval $[0, 1]$.

Players now base their decisions on their own, subjective assessment of their survival chances. Fortunately, since $\pi(p)$ is a monotonic and continuous function of the actual probabilities, the players' decision problem simplifies again to a single, elementary lottery, where the objective (estimated) survival probability $p_i$ is now replaced by the subjective probability, or decision weight $\pi(p_i)$. As under the cumulative prospect theory, we assume that the decision weights sum to one. Hence, the decision weight attached to not surviving this round is given by $1 - \pi(p_i)$.

Expected utility maximisation implies again a probit model with observations $y_i = 0$ (stop) if $y_i^* < 0$ and $y_i = 1$ (continue) if $y_i^* \geq 0$, where $y_i^*$ is now given by

$$y_i^* = \pi(p_i) - p_i^* + \epsilon_i, \tag{19}$$

where $p_i^*$ is again the critical probability defined in (3).

Table 12 reports the parameter estimates for the various utility specifications. For a given value of $W$, the estimate for $\gamma$ under CRRA increases if we replace true probabilities with the corresponding decision weights (compare Tables 6 and 12). Similarly, under CARA the estimate of $\gamma$ increases further. This is explained by the bias in assessing the survival chances. The bias is illustrated in Figure 6, which depicts the implied estimate for the function $\pi(p)$. For every observation $i$ we have that $\pi(p_i) > p_i$, and in many cases the perceived survival probability is substantially larger than the objective probability. If that is the case, a higher value for $\gamma$ is needed to explain the observed stop decisions in the data.

Also, for the relevant range of $p_i$ we observe that $\pi(p_i)$ is flatter than the 45°-line, indicating that the decision weight is rather insensitive to changes in the objective survival probability. This suggests that it may be hard for players to assess the effects of changes in the number of balls drawn and the number of LINGO possibilities on their odds.

Table 13 expresses the increase in the estimated degree of risk aversion in terms of elementary lotteries. The pattern is very similar for the various utility specifications. Therefore, Table 13 only includes critical probabilities based on the estimated CARA specification. At the critical probability $p^*$ players are indifferent between receiving $x$ with certainty, or $2x$ with probability $p^*$ and $a$ with probability $1-p^*$. A comparison with the results in Table 9 shows that the *perceived* survival probability (or decision weight) in a third final ($a = 0$) with $f8000$ at stake has to rise from at least 0.72 to at least 0.89 in order for the players to continue.

Table 14 shows the estimates of the PROBIT model

$$y_i^* = \alpha \left( \frac{\pi(p_i) - p_i^*}{\sigma} \right) + \beta z_i + \epsilon_i \,, \tag{20}$$

where $z_i$ includes "rules of thumb" variables. The $p_i^*$ are computed at the maximum likelihood estimate for the CARA specification reported in Table 12. The results are very similar to those for the case in which we stick to the survival probabilities rather than the decision weights (compare with Table 11). Again, the estimate for $\alpha$ is close to one in all cases, while in the last two columns STAKE, LAST and W0 are all significant. This confirms our earlier conjecture that heterogeneity in risk attitudes and abilities may play a role.

# 8 Concluding Remarks

One of the main problems in economics is the assessment of individuals' risk attitudes. In this paper we have used data from the television game LINGO to estimate the degree of risk aversion using CRRA and CARA utility specifications. We also estimated specifications in which the survival probabilities were replaced by decision weights.

We find robust evidence of substantial risk aversion. Moreover, the estimated degree of risk aversion is likely to provide a lower bound on the true degree of risk aversion for the reasons given in the Introduction. However, substantial care needs to be taken in interpreting estimated CRRA coefficients in terms of the degree of risk aversion. This is illustrated by the fact that the estimated RRA coefficient increases if we condition on a higher initial wealth level. Yet, in terms of elementary lotteries the effect would be almost negligible.

Another finding is that players display a strong tendency to overestimate their chances of success. Most likely, this bias can be attributed to overconfidence in the ability to solve word puzzles. This explanation would square well with empirical evidence elsewhere in the literature that individuals are overconfident in many situations involving decision making under uncertainty.

Data limitations forced us to make a few simplifying assumptions which in future work – as more data become available – we would like to relax. We assumed that players were identical in their abilities and their risk attitudes. For our purpose, which is to develop some sense of how risk averse individuals are on average, these assumptions are probably not too harmful. Nevertheless, we find some evidence that suggests that differences in abilities and risk attitudes may be important.

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Table 1: Summary statistics

| VARIABLE | Average | Standard Deviation | Min | Max | # Obs |
|---|---|---|---|---|---|
| *Statistics per show* | | | | | |
| SEX | 0.2 | 0.8 | -1 | 1 | 734 |
| AGE | 32.3 | 8.7 | 18 | 70 | 401 |
| LOSER | 382 | 689 | 0 | 6300 | 720 |
| JACKPOT | 2194 | 2777 | 0 | 20100 | 720 |
| FINAL | 1.4 | 0.6 | 1 | 3 | 734 |
| W0 | 481 | 106 | 150 | 950 | 734 |
| W1 | 2925 | 5097 | 0 | 27200 | 734 |
| WINJACK | 439 | 1435 | 0 | 20450 | 722 |
| *Statistics per team* | | | | | |
| SEX | 0.2 | 0.8 | -1 | 1 | 489 |
| AGE | 32.5 | 9.1 | 18 | 70 | 271 |
| W1 | 4294 | 5681 | 0 | 27200 | 500 |
| TOTAL | 5158 | 5889 | 0 | 28650 | 500 |

*Notes*: SEX describes the sex composition of a couple: -1, if both players are male, 1, if both are female, and 0, otherwise; AGE is the age of a participant (the number of observations refers to the number of participants for which we know AGE, not the number of teams); LOSER is the money won by the losers of the pre-final; JACKPOT is the amount of money in the jackpot at the end of the pre-final; FINAL is the number of finals played including this one; W0 is the initial stake in the final; W1 are the total gains in the final, excluding jackpot wins; WINJACK are the gains from the jackpot; TOTAL gives the total gains of a team, possibly accumulated over different games and including jackpot wins. The first part of the table pertains to all games; the second part gives statistics per couple. The number of observations can be different from the total of 734 due to missing values for some early games.

Table 2: Frequency distribution of balls to be drawn

| | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| OVERALL | 0.15 | 0.32 | 0.22 | 0.14 | 0.081 | 0.089 |
| W0 $\leq$ 400 | 0.15 | 0.28 | 0.23 | 0.14 | 0.081 | 0.120 |
| W0 > 400 | 0.15 | 0.35 | 0.22 | 0.13 | 0.080 | 0.073 |

*Notes*: The entries report the frequency of the number of balls to be drawn from the urn per round. The OVERALL line is the average over all plays. The other lines split the sample according to initial stakes (W0 $\leq>$ 400).

Table 3: Finals separated in winners, losers and stoppers

| FINAL | 1 | | 2 | | 3 | |
|---|---|---|---|---|---|---|
| | ABS | PERC | ABS | PERC | ABS | PERC |
| WINNER | 55 | 11 | 16 | 9 | 4 | 7 |
| STOPPER | 89 | 18 | 43 | 25 | 22 | 36 |
| LOSER | 356 | 71 | 114 | 66 | 35 | 57 |
| TOTAL | 500 | 100 | 173 | 100 | 61 | 100 |

*Notes*: Entries report the number of finals that end with a couple winning all five rounds (WINNER), couples deciding to stop (STOPPER), and couples ending the round with nothing (LOSER). ABS is the absolute number of finals, and PERC the percentage of total.

Table 4: Odds at decision moments

| | Average | Standard Deviation | Min | Max |
|---|---|---|---|---|
| STOPPERS | 0.62 | 0.08 | 0.44 | 0.86 |
| PLAYERS | 0.71 | 0.11 | 0.46 | 0.88 |

*Notes*: The entries show the survival probabilities, when couples made their last play decision, or when they stopped.

Table 5: Probit Regressions for Rules of Thumb

| CONST | PROB | STAKE | FINAL | BALLS | BAD | LAST | W0 | $\ln L$ |
|---|---|---|---|---|---|---|---|---|
| -0.98 | – | -0.37 | -0.37 | 0.09 | -0.17 | 0.33 | 1.87 | -263.68 |
| (1.05) | | (0.04) | (0.09) | (0.03) | (0.05) | (0.12) | (0.73) | |
| 0.70 | – | -0.28 | -0.37 | 0.08 | -0.16 | – | 1.14 | -266.80 |
| (0.80) | | (0.03) | (0.09) | (0.03) | (0.05) | | (0.68) | |
| 1.31 | -4.21 | -0.37 | -0.36 | 0.14 | -0.42 | 0.35 | 1.90 | -263.59 |
| (5.82) | (9.93) | (0.05) | (0.09) | (0.12) | (0.59) | (0.13) | (0.74) | |
| -0.18 | 3.61 | -0.30 | -0.37 | – | – | – | 1.42 | -268.03 |
| (0.53) | (0.72) | (0.03) | (0.09) | | | | (0.64) | |

*Notes*: Dependent variable is the play/stop decision (1/0). Explanatory variables are a constant (CONST), the probability to survive next round (PROB), the prize money at stake (STAKE), the number of times the team appeared in the final including this final (FINAL), the number of balls still in the urn (BALLS), the number of direct LINGO possibilities (BAD), the round of play in this final (LAST) and the amount with which the team enters the final (W0). Standard errors are in parentheses. The last column reports the maximised value of the loglikelihood function.

Table 6: Parameter Estimates of CRRA Utility Function

| $W$ | $\gamma$ | $a_1$ | $a_2$ | $\sigma$ | $\ln L$ |
|---|---|---|---|---|---|
| 0 | 0.41 | 1.86 | 1.49 | 0.23 | -284.676 |
| | (0.06) | (0.26) | (0.26) | (0.03) | |
| 2 | 0.93 | 1.94 | 1.57 | 0.20 | -269.683 |
| | (0.10) | (0.22) | (0.23) | (0.02) | |
| 10 | 1.97 | 1.96 | 1.56 | 0.20 | -265.502 |
| | (0.22) | (0.22) | (0.25) | (0.02) | |
| 20 | 3.16 | 1.96 | 1.55 | 0.20 | -264.103 |
| | (0.36) | (0.23) | (0.26) | (0.02) | |
| 50 | 6.66 | 1.96 | 1.54 | 0.21 | -263.473 |
| | (0.60) | (0.26) | (0.26) | (0.03) | |
| 100 | 12.46 | 1.95 | 1.53 | 0.21 | -263.265 |
| | (1.48) | (0.24) | (0.27) | (0.02) | |

*Notes*: Dependent variable is the play/stop decision (1/0). $\gamma$ is the coefficient of relative risk aversion in the CRRA model. $W$ denotes the reference level of wealth in units of $f1000$; $a_1$ and $a_2$ are the equivalent guilder amounts of the "comeback" utilities (in units of 1000 guilders). $\ln L$ is the value of the log likelihood at the optimum, and $\sigma$ is the standard deviation of the error term. Standard errors are in parentheses. The parameters have been estimated by maximum likelihood conditional on the wealth parameter $W$ and using the survival probabilities $p_i$. Estimates and standard errors are given conditional on several values of $W$. The number of observations is $N = 888$.

Table 7: Constant Relative Risk Aversion: Subsample Results

| $W$ | $\gamma$ | $\sigma$ | $N$ | $\ln L$ |
|---|---|---|---|---|
| 50 | 4.95 | 0.17 | 83 | -38.354 |
| | (1.54) | (0.03) | | |

*Notes*: Dependent variable is the play/stop decision (1/0). $\gamma$ is the coefficient of relative risk aversion. See Table 6 for explanatory notes. Estimates are based on the subsample of teams that are in the final for the third, and last, time.

Table 8: Constant Absolute Risk Aversion

| | $\gamma$ | $a_1$ | $a_2$ | $\sigma$ | $N$ | $\ln L$ |
|---|---|---|---|---|---|---|
| All games | 0.12 | 1.95 | 1.53 | 0.21 | 888 | -263.065 |
| | (0.01) | (0.24) | (0.27) | (0.02) | | |
| Third finals | 0.09 | | | 0.17 | 83 | -38.366 |
| | (0.03) | | | (0.04) | | |

*Notes*: Dependent variable is the play/stop decision (1/0). $\gamma$ is the coefficient of absolute risk aversion in the CARA model. $a_1$ and $a_2$ are the equivalent guilder amount of the "comeback" utilities (in $f1000$). $\ln L$ is the value of the log likelihood at the optimum, and $\sigma$ is the standard deviation of the error term. Standard errors are in parentheses. "All games" uses all data, while "Third finals" is only based on teams that are in the final for the third and last time.

Table 9: Critical probabilities

| Parameters | | | Stakes ($x$) | | | | |
|---|---|---|---|---|---|---|---|
| $\gamma$ | $W$ | $a$ | 0.5 | 1 | 2 | 4 | 8 |
| **CRRA** | | | Critical probabilities ($p^*$) | | | | |
| 0.41 | 0 | 0 | 0.66 | 0.66 | 0.66 | 0.66 | 0.66 |
| 1.97 | 10 | 0 | 0.52 | 0.54 | 0.58 | 0.64 | 0.72 |
| 6.66 | 50 | 0 | 0.52 | 0.53 | 0.56 | 0.62 | 0.72 |
| 0.41 | 0 | 1.86 | 0 | 0 | 0.08 | 0.42 | 0.53 |
| 1.97 | 10 | 1.96 | 0 | 0 | 0.02 | 0.43 | 0.62 |
| 6.66 | 50 | 1.96 | 0 | 0 | 0.03 | 0.42 | 0.62 |
| **CARA** | | | | | | | |
| 0.116 | — | 0 | 0.51 | 0.53 | 0.56 | 0.61 | 0.72 |
| 0.116 | — | 1.95 | 0 | 0 | 0.04 | 0.42 | 0.63 |

*Notes*: The entries report the critical probabilities $p^*$ for various parameter combinations of the CRRA and CARA utility functions and for various stakes $x$. The parameter $a$ is the option value for teams that have their first appearance in the final. See Tables 6 and 8 for further explanation of the parameters. The critical probabilities are computed as $p^* = (U(x) - U(a))/(U(2x) - U(a))$ and denote the lowest win probability at which an agent will prefer the lottery with payout $(2x, a; p^*, 1-p^*)$ over the sure amount $x$.

Table 10: Model Evaluation

| Actual | Predicted Stop | Predicted Play | Marginal | Misclassified |
|---|---|---|---|---|
| Stop | 8 | 9 | 17 | 55 |
| Play | 5 | 78 | 83 | 6 |
| Marginal | 13 | 87 | 100 | 14 |

*Notes*: Entries report the percentage of cases with actual or predicted play or stop decisions. The column "Misclassified" contains the wrongly predicted cases as a percentage of stoppers, players, and overall, respectively.

Table 11: Expected Utility versus Rules of Thumb

| Variable | | | | |
|---|---|---|---|---|
| CONST | 0.05 | 0.26 | -3.63 | 2.53 |
| | (0.08) | (0.55) | (1.19) | (5.68) |
| PROB | | -0.24 | | -11.5 |
| | | (1.30) | | (10.4) |
| STAKE | | -0.09 | -0.19 | -0.19 |
| | | (0.06) | (0.06) | (0.06) |
| FINAL | | -0.01 | 0.09 | 0.11 |
| | | (0.13) | (0.13) | (0.14) |
| BALLS | | | 0.03 | 0.16 |
| | | | (0.03) | (0.12) |
| BAD | | | 0.06 | -0.61 |
| | | | (0.08) | (0.61) |
| LAST | | | 0.58 | 0.63 |
| | | | (0.14) | (0.15) |
| W0 | | 1.06 | 2.06 | 2.18 |
| | | (0.65) | (0.75) | (0.77) |
| PSTAR | 0.97 | 0.80 | 0.91 | 0.95 |
| | (0.09) | (0.24) | (0.20) | (0.21) |
| $\ln L$ | -262.879 | -259.763 | -251.601 | -250.998 |

*Notes*: Dependent variable is the play/stop decision. PSTAR is the expected utility decision variable $\frac{p_i - p_i^*}{\sigma}$. Other explanatory variables are as explained in Section 4.

Table 12: Risk Aversion with Decision Weights

| $W$ | $\gamma$ | $a_1$ | $a_2$ | $\mu$ | $\omega$ | $\sigma$ | $\ln L$ |
|---|---|---|---|---|---|---|---|
| **CRRA** | | | | | | | |
| 2 | 2.21 | 1.03 | 0.74 | -1.25 | 0.93 | 0.13 | -260.527 |
| | (0.64) | (0.26) | (0.24) | (0.65) | (0.59) | (0.02) | |
| 10 | 4.31 | 1.47 | 1.03 | -0.69 | 0.76 | 0.19 | -259.711 |
| | (1.26) | (0.33) | (0.34) | (0.38) | (0.41) | (0.04) | |
| 20 | 6.98 | 1.57 | 1.10 | -0.58 | 0.70 | 0.21 | -259.525 |
| | (2.00) | (0.34) | (0.36) | (0.33) | (0.36) | (0.04) | |
| 50 | 14.99 | 1.64 | 1.15 | -0.51 | 0.66 | 0.23 | -259.407 |
| | (4.22) | (0.35) | (0.37) | (0.29) | (0.31) | (0.04) | |
| 100 | 28.34 | 1.67 | 1.16 | -0.48 | 0.64 | 0.23 | -259.370 |
| | (7.92) | (0.35) | (0.37) | (0.28) | (0.30) | (0.04) | |
| **CARA** | | | | | | | |
| | 0.27 | 1.70 | 1.18 | -0.45 | 0.62 | 0.24 | -259.336 |
| | (0.07) | (0.35) | (0.38) | (0.27) | (0.28) | (0.04) | |

*Notes*: Dependent variable is the play/stop decision (1/0). $\gamma$ is the coefficient of relative (absolute) risk aversion in the CRRA (CARA) model. Probabilities are transformed to decision weights according to the double LOGIT transformation (18) with parameters $\mu$ and $\omega$. See Tables 6 and 8 for further explanatory notes. For the CRRA model with $W = 0$ the optimisation algorithm is stuck at a boundary solution with $\gamma = 1$.

Table 13: Critical probabilities for **CARA**

| Parameters | | Stakes ($x$) | | | | |
|---|---|---|---|---|---|---|
| $\gamma$ | $a$ | 0.5 | 1 | 2 | 4 | 8 |
| 0.267 | 0 | 0.53 | 0.57 | 0.63 | 0.74 | 0.89 |
| 0.267 | 1.70 | 0 | 0 | 0.17 | 0.56 | 0.83 |

*Notes*: The entries report, for various stakes $x$, the critical probability $p^*$ for the estimated parameter combination of the CARA utility specification. The critical probability is computed as $p^* = (U(x) - U(a))/(U(2x) - U(a))$ and denotes the lowest win probability at which an agent will prefer the lottery with payout $(2x, a; p^*, 1 - p^*)$ over the sure amount $x$. For further description of the parameters, see Table 9.

Table 14: Expected Utility versus Rules of Thumb: Decision Weights

| Variable | | | | |
|---|---|---|---|---|
| CONST | -0.003 | -0.11 | -4.22 | 2.42 |
| | (0.08) | (0.53) | (1.23) | (5.69) |
| PROB | | 0.03 | | -12.5 |
| | | (1.18) | | (10.4) |
| STAKE | | -0.03 | -0.14 | -0.14 |
| | | (0.07) | (0.07) | (0.07) |
| FINAL | | -0.05 | 0.09 | 0.11 |
| | | (0.12) | (0.12) | (0.88) |
| BALLS | | | 0.02 | 0.16 |
| | | | (0.03) | (0.12) |
| BAD | | | 0.04 | -0.69 |
| | | | (0.07) | (0.61) |
| LAST | | | 0.69 | 0.76 |
| | | | (0.15) | (0.16) |
| W0 | | 0.80 | 2.04 | 2.17 |
| | | (0.66) | (0.75) | (0.77) |
| PSTAR | 1.00 | 0.93 | 1.13 | 1.18 |
| | (0.09) | (0.26) | (0.23) | (0.24) |
| $\ln L$ | -259.335 | -258.580 | -248.290 | -247.582 |

*Notes*: Dependent variable is the play/stop decision. PSTAR is the expected utility decision variable $\frac{\pi(p_i)-p_i^*}{\sigma}$. Other explanatory variables are as explained in Section 4.

Figure 1: Lotteries and decisions

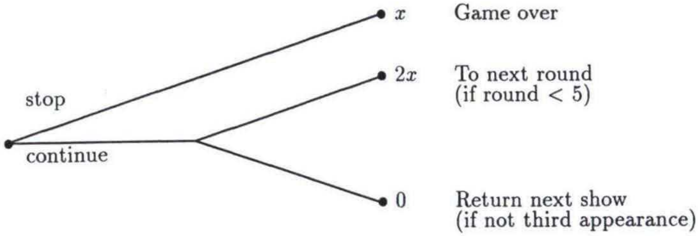
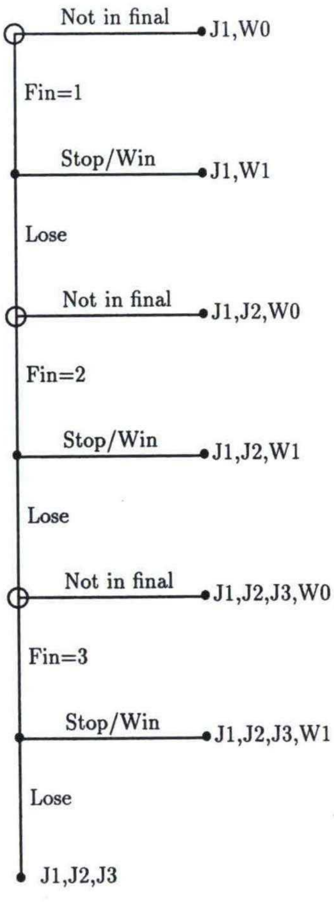



Figure 2: LINGO board

| | | | | |
|---|---|---|---|---|
| X | | X | | X |
| | X | X | X | |
| X | X | | X | X |
| | X | X | X | |
| X | | X | | X |

Figure 3: Flow chart and sources of gains for first-time participants




This figure depicts all the possible ways in which a couple that appears in their first pre-final can go through the game. It also shows the possible sources of money gains when the couple leaves the game. W0 (W1) is the stake at the end of the pre-final (final). J1, J2, J3 is the jackpot gain in the first, second and third pre-final, respectively.

Figure 4: Two-round game

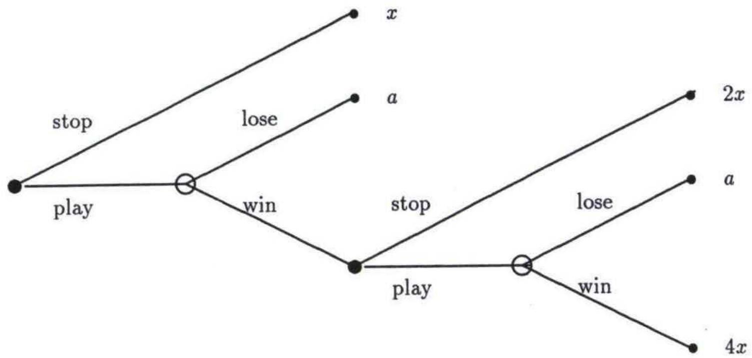
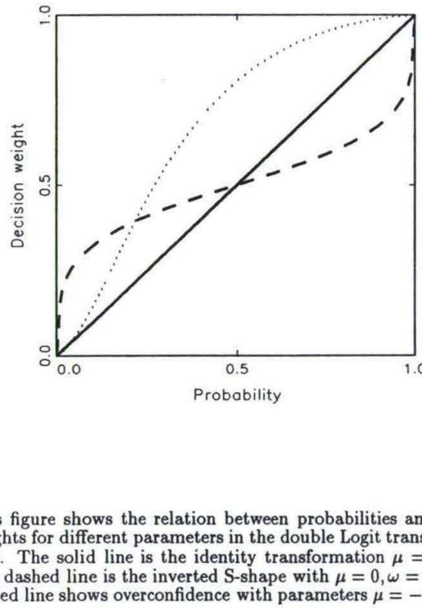
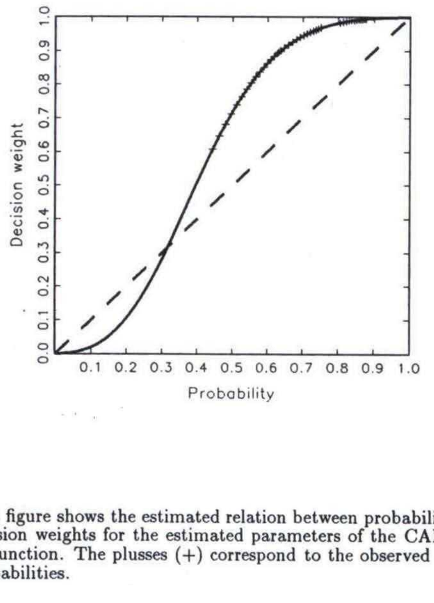


Figure 5: Decision weights and probabilities




This figure shows the relation between probabilities and decision weights for different parameters in the double Logit transformation (18). The solid line is the identity transformation $\mu = 0, \omega = 1$. The dashed line is the inverted S-shape with $\mu = 0, \omega = 3$, and the dotted line shows overconfidence with parameters $\mu = -1, \omega = 0.7$.

Figure 6: Empirical Decision Weights




This figure shows the estimated relation between probabilities and decision weights for the estimated parameters of the CARA utility function. The plusses (+) correspond to the observed survival probabilities.

# Appendix: NOT for publication – available upon request

## A Probabilities

The LINGO board has 25 squares. In the initial situation 16 are covered (X) and 9 positions are open (1, ..., 9). The initial position is the same in each game. It is shown in Figure 7. The game is lost, if a column, row or main diagonal is completely covered. This is called LINGO. In the initial position ball 5 would give LINGO.

Figure 7: LINGO board

| | | | | |
|---|---|---|---|---|
| X | 1 | X | 2 | X |
| 3 | X | X | X | 4 |
| X | X | 5 | X | X |
| 6 | X | X | X | 7 |
| X | 8 | X | 9 | X |

A player has to draw a specified number of balls from an urn. Initially the urn contains 36 balls:

- Nine balls numbered 1 through 9 corresponding to the open squares on the board.
- One golden ball. When a player draws the golden ball, she may stop drawing new balls.
- 26 balls numbered zero. The "zeros" are harmless, because they do not appear on the LINGO board.

If a player draws any of the numbered balls, two additional LINGO chances open up. Which of the numbered balls is drawn is irrelevant, because the initial position is completely symmetric. For instance, if ball 1 is drawn, then balls 2 and 8 give LINGO, while ball 9 becomes harmless. From this position with 3 LINGO chances the game transposes to a position with five balls giving LINGO, when either of balls 3, 4, 6 or 7 is drawn.

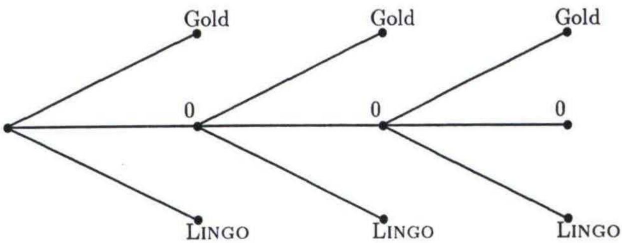
The easiest situation to analyse is when there are five LINGO possibilities on the board. The position is shown in Figure 8. Suppose that at the start of a 5 ball LINGO round the urn contains $n$ balls. One of them is the golden ball, 5 of them are numbered balls that give LINGO, while the remaining $n-6$ balls are zeros.[17]

Figure 8: 5-ball LINGO position

| | | | | |
|---|---|---|---|---|
| X | X | X | | X |
| X | X | X | X | |
| X | X | | X | X |
| | X | X | X | X |
| X | | X | X | X |

A player must draw $k$ balls from the urn. The minimum is $k=1$, when the five letter word was guessed correctly at the first try. The maximum is $k=6$, when the the required word was not found after five attempts. Let $P_5(k,n)$ be the probability of surviving this round of LINGO if $k$ balls must drawn from an urn containing $n$ balls. The possible outcomes of the drawing process are shown in Figure 9.

Figure 9: Evolution of 5-ball LINGO




The tree has three branches, depending on drawing Gold, LINGO, or Zero. The round ends succesfully after drawing the golden ball. The player loses after drawing

[17] In the figure we have also covered the cells of balls 7 and 9. Because after ball 3 is drawn, ball 7 does not change anything on the board, we assume that ball 7 is taken out of the urn and replaced by a zero. Similarly, after ball 1 was drawn, we assume that ball 9 was replaced by a zero.

LINGO, and continues after drawing a zero. The probability of not having LINGO with the first ball is

$$\begin{aligned} P_5(1,n) &= \Pr[\text{Gold}_1] + \Pr[\text{Zero}_1] \\ &= \frac{1}{n} + \frac{n-6}{n}. \end{aligned} \tag{21}$$

The probability for surviving the next ball is

$$\begin{aligned} P_5(2,n) &= \Pr[\text{Gold}_1] + \Pr[\text{Zero}_1]\left(\Pr[\text{Gold}_2|\text{Zero}_1] + \Pr[\text{Zero}_2|\text{Zero}_1]\right) \\ &= \frac{1}{n} + \frac{n-6}{n}\left(\frac{1}{n-1} + \frac{n-7}{n-1}\right). \end{aligned} \tag{22}$$

Since the game only continues upon drawing a zero, the general formula for surviving after $k > 1$ balls follows directly as

$$P_5(k,n) = w_5(k,n) + \sum_{j=0}^{k-1} \frac{w_5(j,n)}{n-j}, \tag{23}$$

where the weights $w_5(k,n)$ are defined recursively by

$$\begin{aligned} w_5(0,n) &= 1, \\ w_5(k,n) &= w_5(k-1,n)\frac{n-k-5}{n-k+1}, \qquad k > 0. \end{aligned}$$

Next consider a LINGO board where there are three direct LINGO possibilities. In that case only one of the numbered balls 1-8 has been drawn. The round ends by either drawing LINGO (lose), or by drawing Gold (win). The game transforms into 5-ball LINGO if one of the four numbered balls is drawn that do not directly give LINGO. If the urn contains $n$ balls, then 4 are numbered balls, 3 are LINGO balls, 1 is gold, and the remaining $n-8$ are Zero's. The probability of not getting LINGO with the first ball is

$$\begin{aligned} P_3(1,n) &= \Pr[\text{Gold}_1] + \Pr[\text{Number}_1] + \Pr[\text{Zero}_1] \\ &= \frac{1}{n} + \frac{4}{n} + \frac{n-8}{n}. \end{aligned} \tag{24}$$

If ball 1 is a numbered ball the probability of not getting LINGO with the second ball is equal to $P_5(1, n-1)$, *i.e.* the probability of surviving one draw in a five ball LINGO game with $n-1$ balls in the urn. Therefore the probability of surviving, when two balls must be drawn is

$$\begin{aligned} P_3(2,n) &= \Pr[\text{Gold}_1] + \Pr[\text{Number}_1] \times P_5(1,n-1) \\ &\qquad + \Pr[\text{Zero}_1]\left(\Pr[\text{Gold}_2] + \Pr[\text{Number}_2] + \Pr[\text{Zero}_2]\right) \\ &= \frac{1}{n} + \frac{4}{n}P_5(1,n-1) + \frac{n-8}{n}\left(\frac{1}{n-1} + \frac{4}{n-1} + \frac{n-9}{n-1}\right). \end{aligned} \tag{25}$$

Because of the recursive structure the general formula for surviving with $k > 1$ is

$$\begin{aligned} P_3(k,n) &= w_3(k,n) + \sum_{j=0}^{k-1} \frac{w_3(j,n)}{n-j} \\ &\qquad + 4\left(\sum_{j=0}^{k-2} \frac{w_3(j,n)}{n-j} P_5(k-j-1,n-j-1) + \frac{w_3(k-1,n)}{n-k+1}\right). \end{aligned} \tag{26}$$

where the weights $w_3(k,n)$ are defined recursively by

$$\begin{aligned} w_3(0,n) &= 1, \\ w_3(k,n) &= w_3(k-1,n)\frac{n-k-7}{n-k+1}, \qquad k > 0. \end{aligned}$$

Finally, when no numbered balls have been drawn, the LINGO board is still in its original position as shown in Figure 7. When one of the 8 numbered balls 1 through 8 is drawn, the game transposes to the "3 ball LINGO" position analysed above. The derivation of the probabilities is also completely analogous to "3 ball LINGO". The urn contains $n$ balls, one of which is the golden ball, one gives LINGO, 8 transpose to "3 ball LINGO", and the remaining $n-10$ are zero. The probabilities are given by

$$P_1(1,n) = \frac{n-1}{n}, \tag{27}$$

and for $k > 1$:

$$\begin{aligned} P_1(k,n) &= w_1(k,n) + \sum_{j=0}^{k-1} \frac{w_1(j,n)}{n-j} \\ &\qquad + 8\left(\sum_{j=0}^{k-2} \frac{w_1(j,n)}{n-j} P_3(k-j-1,n-j-1) + \frac{w_1(k-1,n)}{n-k+1}\right), \end{aligned} \tag{28}$$

where the weights $w_1(k,n)$ are defined recursively by

$$\begin{aligned} w_1(0,n) &= 1, \\ w_1(k,n) &= w_1(k-1,n)\frac{n-k-9}{n-k+1}, \qquad k > 0. \end{aligned}$$

# B Proof of Lemma 1

## B.1 CRRA utility

We distinguish between the case with $0 < \gamma < 1$ and the case with $\gamma > 1$. Suppose first that $0 < \gamma < 1$. We can rewrite the critical probability $p^*$ in (5) as:

$$p^*(y,\lambda) = \frac{(1+y)^\delta - 1}{(1+\lambda y)^\delta - 1},$$

where (remember that, by assumption, $x > a \geq 0$)

$$1 > \delta \equiv 1 - \gamma > 0, y \equiv \frac{x-a}{W+a} > 0, \lambda \equiv \frac{2x-a}{x-a} > 1.$$

Differentiating yields:

$$\frac{\partial p^*(.)}{\partial y} = \frac{\delta(1+y)^{\delta-1}\left[(1+\lambda y)^\delta - 1\right] - \lambda\delta(1+\lambda y)^{\delta-1}\left[(1+y)^\delta - 1\right]}{\left[(1+\lambda y)^\delta - 1\right]^2}.$$

The numerator (divided by $\delta$) can be written as:

$$\begin{aligned}
& (1+y)^{\delta-1}\left[(1+\lambda y)^\delta - 1\right] - \lambda(1+\lambda y)^{\delta-1}\left[(1+y)^\delta - 1\right] \\
= \; & (1+y)^{\delta-1}(1+\lambda y)^\delta - (1+y)^{\delta-1} - \lambda(1+\lambda y)^{\delta-1}(1+y)^\delta + \lambda(1+\lambda y)^{\delta-1} \\
= \; & \left[\frac{1}{1+y} - \frac{\lambda}{1+\lambda y}\right]\left[(1+y)(1+\lambda y)\right]^\delta + \left[\frac{\lambda}{(1+\lambda y)^{1-\delta}} - \frac{1}{(1+y)^{1-\delta}}\right] \\
= \; & (1-\lambda)\left[(1+y)(1+\lambda y)\right]^{\delta-1} + \frac{\lambda(1+y)^{1-\delta} - (1+\lambda y)^{1-\delta}}{\left[(1+y)(1+\lambda y)\right]^{1-\delta}} \\
= \; & \frac{1 - \lambda + \lambda(1+y)^{1-\delta} - (1+\lambda y)^{1-\delta}}{\left[(1+y)(1+\lambda y)\right]^{1-\delta}}.
\end{aligned}$$

The numerator of the latter expression is zero for $y = 0$. Differentiating this numerator with respect to $y$ yields:

$$\lambda(1-\delta)\left[\frac{1}{(1+y)^\delta} - \frac{\lambda}{(1+\lambda y)^\delta}\right] > 0, \text{ if } y > 0.$$

Hence, the numerator of $\partial p^*(.)/\partial y$ is positive if $y > 0$. Hence, if $y > 0$, $\partial p^*(y,\lambda)/\partial y > 0$. From the definition of $y$ it then follows that $\partial p^*/\partial W < 0$.

To find the effect of the stake on the critical probability, differentiate $p^*$ with respect to $x$:

$$\frac{\partial p^*}{\partial x} = \frac{\partial p^*}{\partial y}\frac{\partial y}{\partial x} + \frac{\partial p^*}{\partial \lambda}\frac{\partial \lambda}{\partial x} > 0,$$

because $\partial p^*/\partial y > 0$, $\partial y/\partial x > 0$, $\partial p^*/\partial\lambda < 0$ and $\partial\lambda/\partial x \leq 0$.

Now, suppose that $\gamma > 1$. We can rewrite $p^*$ in (5) as:

$$p^*(y,\lambda) = \frac{1-(1+y)^{-\eta}}{1-(1+\lambda y)^{-\eta}}, \quad \eta \equiv \gamma - 1 > 0.$$

Differentiating yields:

$$\frac{\partial p^*(.)}{\partial y} = \frac{\eta(1+y)^{-(1+\eta)}\left[1-(1+\lambda y)^{-\eta}\right] - \lambda\eta(1+\lambda y)^{-(1+\eta)}\left[1-(1+y)^{-\eta}\right]}{\left[1-(1+\lambda y)^{-\eta}\right]^2},$$

The numerator (divided by $\eta$) can be written as:

$$\begin{aligned}
& (1+y)^{-(1+\eta)} - (1+y)^{-(1+\eta)}(1+\lambda y)^{-\eta} - \lambda(1+\lambda y)^{-(1+\eta)} + \lambda(1+\lambda y)^{-(1+\eta)}(1+y)^{-\eta} \\
= \ & (1+y)^{-(1+\eta)} - \lambda(1+\lambda y)^{-(1+\eta)} + \left[\frac{\lambda}{1+\lambda y} - \frac{1}{1+y}\right]\left[(1+y)(1+\lambda y)\right]^{-\eta} \\
= \ & (1+y)^{-(1+\eta)} - \lambda(1+\lambda y)^{-(1+\eta)} + (\lambda-1)\left[(1+y)(1+\lambda y)\right]^{-(1+\eta)} \\
= \ & \frac{(1+\lambda y)^{1+\eta} - \lambda(1+y)^{1+\eta}}{\left[(1+y)(1+\lambda y)\right]^{1+\eta}} + \frac{\lambda - 1}{\left[(1+y)(1+\lambda y)\right]^{1+\eta}}
\end{aligned}$$

The numerator of the latter expression is zero for $y = 0$. Differentiating this numerator with respect to $y$ yields:

$$\lambda(1+\eta)\left[(1+\lambda y)^{\eta} - (1+y)^{\eta}\right] > 0, \text{ if } y > 0.$$

Hence, the numerator of $\partial p^*(.)/\partial y$ is positive if $y > 0$. Hence, if $y > 0$, $\partial p^*(y,\lambda)/\partial y > 0$. From the definition of $y$ it then follows that $\partial p^*/\partial W < 0$.

We can again show that $\partial p^*/\partial\lambda < 0$. Hence, again,

$$\frac{\partial p^*}{\partial x} = \frac{\partial p^*}{\partial y}\frac{\partial y}{\partial x} + \frac{\partial p^*}{\partial\lambda}\frac{\partial\lambda}{\partial x} > 0,$$

which completes the proof.

## B.2 CARA utility

The condition $p_2^* \geq p_1^*$ can be rewritten as

$$U^2(2x) - U(4x)U(x) + U(a)[U(x) + U(4x) - 2U(2x)] \geq 0. \quad (29)$$

Use the definition of CARA utility to write this as

$$\begin{aligned}
[\exp(-4\gamma x) - \exp(-5\gamma x)] + \exp(-\gamma a)[\exp(-4\gamma x) + \exp(-\gamma x) - 2\exp(-2\gamma x)] &\geq 0 \Leftrightarrow \\
[\exp(\gamma x) - 1] + \exp(-\gamma a)[\exp(\gamma x) + \exp(4\gamma x) - 2\exp(3\gamma x)] &\geq 0 \quad (30)
\end{aligned}$$

Denote the left-hand side of this equation by the function $k(x)$. Hence,

$$k'(x) = \gamma \exp(\gamma x) + \exp(-\gamma a)[\gamma \exp(\gamma x) + 4\gamma \exp(4\gamma x) - 6\gamma \exp(3\gamma x)],$$

$$k''(x) = \gamma^2 \exp(\gamma x) + \exp(-\gamma a)[\gamma^2 \exp(\gamma x) + 16\gamma^2 \exp(4\gamma x) - 18\gamma^2 \exp(3\gamma x)],$$

$$k'''(x) = \gamma^3 \exp(\gamma x) + \exp(-\gamma a)[\gamma^3 \exp(\gamma x) + 64\gamma^3 \exp(4\gamma x) - 54\gamma^3 \exp(3\gamma x)].$$

Note that $k(0) = 0$, $k'(0) = \gamma[1 - \exp(-\gamma a)] \geq 0$, $k''(0) = \gamma^2[1 - \exp(-\gamma a)] \geq 0$ and, clearly, $k'''(x) > 0, \forall x \geq 0$. Hence, $k''(x) > 0, \forall x > 0$, hence $k'(x) > 0, \forall x > 0$ and, hence $k(x) > 0, \forall x > 0$, which completes the proof.

# C Proof of the induction argument

Let $p_2^* \geq p_1^*, \forall x > a$. We show that the optimal decision at the start of the $n$-round game is the same as the optimal decision at the start of the single-round game.

First we show that if it is optimal to continue at the start of the single-round game, it is also optimal to continue at the start of the $n$ -round game. Optimality of $A = 1$ at the start of the single-round game implies that $(1 - p_1)U(a) + p_1 U(2x) \geq U(x)$. Hence,

$$\begin{aligned} V_n(1) &= (1 - p_1)U(a) + p_1 \mathsf{E}\{\max[U(2x), V_{n-1}(1)]\} \\ &\geq (1 - p_1)U(a) + p_1 U(2x) \\ &\geq U(x) \\ &= V_1(0) = V_n(0), \end{aligned}$$

which confirms the claim.

We show now that, if it is optimal to stop at the start of the single-round game, it is optimal to stop at the start of the $n$-round game. The proof is by induction. Suppose that it is optimal to stop at the start of the single-round game. That is,

$$V_1(1) = (1 - p_1)U(a) + p_1 U(2x) < U(x) = V_1(0). \tag{31}$$

The first step of the induction argument, the optimality of stopping at the start of a single-round game implies the optimality of stopping at the start of the two-round game, has already been shown in the text.

Suppose now that it is optimal to stop at the start of an $(n-1)$-round game. This is the case if and only if,

$$\begin{aligned} V_{n-1}(1) &= (1-p_1)U(a) + p_1 \mathsf{E}\left[\max\{U(2x), V_{n-2}(1,s)\}\right] \\ &< V_{n-1}(0) = V_1(0) = U(x), \end{aligned} \tag{32}$$

where the expectation is taken over all states $s$ (defined by the number of balls drawn so far and the number of LINGO possibilities) that can be reached from the initial state. For the $n$-round game starting from the same initial state, hence with the same initial survival probability $p_1$, one has:

$$V_n(1) = (1-p_1)U(a) + p_1 \mathsf{E}\left[\max\{U(2x), V_{n-1}(1,s)\}\right].$$

Because the survival probabilities are weakly decreasing over the rounds of the game, it follows immediately that, for all possible states $s$ at the start of the second round, $V_{n-1}(1,s) \leq V_{n-1}(1) \leq V_{n-1}(0) = U(x)$. Hence,

$$\begin{aligned} V_n(1) &= (1-p_1)U(a) + p_1 \mathsf{E}\left[\max\{U(2x), V_{n-1}(1,s)\}\right] \\ &\leq (1-p_1)U(a) + p_1 \max\{U(2x), U(x)\} \\ &= (1-p_1)U(a) + p_1 U(2x) \\ &< V_1(0) = V_n(0). \text{ (by (31))} \end{aligned}$$

Hence, if it is optimal to stop at the start of an $(n-1)$-round game, it is also optimal to stop at the start of an $n$-round game with the same initial state. This completes the induction argument.

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